# Instruction for Web Searching: An Empirical Study

Susan M. Colaric

Users searching the Web have difficulty using search engines and developing queries. Searches tend to be simple, and Boolean operators are used infrequently and incorrectly. Users also are unaware that search engines operate differently from other information retrieval systems. Yet, there is little research on effective instructional methods for teaching users how to search the Web. Research has looked at instructional methods for other types of information retrieval, but these systems differ a great deal from the Web. The purpose of this study was to determine what undergraduate students know about search engines and to examine instructional treatments to aid searchers in using a search engine.

Research has shown that users looking for information on the World Wide Web have a difficult time developing search queries and using a search engine.[1–6] Searches tend to be simple, and Boolean operators are used infrequently and incorrectly.[7,8] Users also appear to be unaware that search engines operate differently from other information retrieval systems they may use, such as a library online catalog, and this appears to contribute to inappropriate search queries.[9–11]

How to use a search engine has been taught primarily through examples and short procedural descriptions. In instruction by example, a learner is given a series of worked-out problems and then asked to solve a new problem on his or her own.[12] A review of the help sections of six search engines (AltaVista, Excite, Go, Google, Hotbot, and Northern Lights; December 2000) showed that instruction by example is used to explain how to use the engine. This method focuses on two types of knowledge: declarative and syntactic. *Declarative knowledge* refers to understanding facts, in this case, facts about search engines.[13] *Syntactic knowledge* refers to knowledge of the language units and rules when working with a computer system, in this case, how to structure a search query using terminology the search engine can interpret correctly.[14]

When users understand the appropriate declarative and syntactic knowledge by studying the example and procedural description, they then can develop a query to fit their information need. This may involve incorporating elements described in the help paragraph that were not included in the example or transferring the example to a completely different domain. Instruction by example presumes the learner will be able to match a new problem situation to a formerly en-

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countered situation, retrieve the solution to the previously solved problem, and map the retrieved information onto the new problem.[15]

To date, no research has investigated whether this method is effective in teaching users to search the Web. Recent studies examining user interactions with the Web have identified factors associated with successful searching, including declarative knowledge and syntactic knowledge. But semantic knowledge also may play a role in successfully retrieving information.[16–21] *Semantic knowledge* refers to the user's understanding of the major locations, objects, and actions inside a computer system.[22,23] Sometimes referred to as system knowledge, semantic knowledge represents how learners choose to use system features based on an awareness of their functions and capabilities.[24] Although earlier findings have demonstrated the importance of semantic knowledge when using other information retrieval systems, research into its role in using search engines is lacking.[25–29]

Instruction to increase semantic knowledge has been used successfully in other domains, such as computer programming and automobile brakes, to increase understanding and efficient use of these systems.[30,31] The focus is on explaining how the system works so that users will better understand how it reacts to input and why particular output occurs.[32,33] This has been done with conceptual models, a depiction of the system that helps learners mentally represent the elements of a system while facilitating the construction of associative links between cause-and-effect relationships. As the learner builds a more complete mental image of how a system works, his or her prediction and inference skills develop and strengthen.[34–36]

Richard E. Mayer described a conceptual model as words and/or diagrams of a system that highlight the major objects and actions, as well as the causal relations among them, to assist learners in building a mental model.[37] Illustrations are often used to represent the interactions among elements of the system.[38–39] The use of illustrations allows the user to picture the critical elements of the system while reading explanations of how those elements interact. In all of the studies, instruction to increase semantic knowledge resulted in better inferencing skills and reasoning about how the system operates. However, these studies were done with closed systems that were not difficult to depict visually.

## Hypotheses

The goal of this study was to investigate three instructional methods to determine differences in knowledge acquisition related to three types of knowledge associated with using a search engine. The three instructional methods were instruction by example, conceptual models without illustrations, and conceptual models with illustrations. The three types of knowledge were declarative knowledge, syntactic knowledge, and semantic knowledge. Based on information from the literature review, three hypotheses were developed:

- Hypothesis #1: There will be significant differences in semantic knowledge acquisition among participants receiving different instructional treatments. Participants who receive conceptual models with illustrations should have the highest scores on the posttest, those who receive conceptual models without illustrations should have the next highest scores, and participants who receive instruction by example should have the lowest scores.
- Hypothesis #2: Semantic knowledge will correlate with syntactic knowledge.
- Hypothesis #3: There will be significant differences in syntactic knowledge acquisition among participants receiving different instructional treatments. Participants who receive conceptual models with illustrations should have the highest scores on the posttest, those who receive conceptual models without illustrations should have the next highest scores, and participants who receive instruction by example should have the lowest scores.

## Methodology

This study was a pretest/treatment/posttest study using print-based materials, with the pretest administered during one class period and the treatment and posttest administered during the next class period. Participants were undergraduate students at a major research university. A cluster sample of ten classes was identified based on whether the curriculum for the course included learning to search the Web. A total of 195 students completed the pretest and were randomly assigned to one of the three instructional groups. Class groups were kept intact, and random assignment to treatments was within each class. Nineteen students were not present for the instructional materials and posttest portion of the study, so their scores were removed from all analyses. This resulted in an unequal number of participants in each group: instruction by example had fifty-nine participants, conceptual models without illustrations had sixty-one, and conceptual models with illustrations had fifty-six.

All the materials were developed using published sources of information on how search engines operate.[40–43] The researcher administered the materials to all groups by attending the class during its normal time and day in the second or third week of classes in the spring semester of 2001. Participation in the study was voluntary; informed consent was obtained and no extra credit was given to the students for participating. The pre- and posttest scoring was done by the researcher; no second scorer was used. However, scoring was dichotomous in nature with no room for disagreement.

The independent variable was the instructional method with three levels (instruction by example, instruction by conceptual models without illustrations, and instruction by conceptual models with illustrations). The dependent variable was posttest scores divided into three sections: (1) declarative knowledge of search engines as measured by questions testing the participant's factual knowledge of search engines; (2) syntactic knowledge of search engines as measured by the elements of a search query with regard to a provided search problem; and (3) semantic knowledge of search engines as defined by the participant's explanation of how a search engine works. The pretest served as a baseline measure of prior knowledge. Analysis of covariance (ANCOVA) was used to analyze posttest scores for each type of knowledge across the different instructional materials with the pretest as the covariate. This allowed an examination of treatment effects without the participants' prior knowledge affecting the analysis.

Demographic data for participants were analyzed to determine whether the three instructional groups were similar in terms of gender, age, major area of study, semesters completed, computer ownership, hours per day spent searching the Web, and hours per day spent using e-mail. Chi-square analyses were performed to test for dependence, but no significant differences were found. The homogeneity of these characteristics supported the assumption that differences in posttest scores would most likely be related to instructional materials.

When beginning the data analysis, Levene's test of equality for error variances showed unequal variance. Even with standardizing to a z-score, three participants reported an average of 8 hours per day on e-mail (compared to the group mean of 1.0 hours) and 2.6 hours per day searching the Web (compared to the group mean of 1.7 hours). This was considered significantly different as to distinguish them from the sample on a critical factor. To address the problem, these extreme cases were removed from all analyses allowing an equal variance assumption to be met. The final number of participants used for data analysis was 173.

## Results and Analyses

### *What Did They Already Know?*

The study participants appeared to have some prior knowledge of search engines. As shown in table 1, most (67%) under-

**TABLE 1**
**Pretest: Declarative Knowledge**

| Question | Correct n | Correct % | Incorrect n | Incorrect % | Don't know n | Don't know % |
|---|---|---|---|---|---|---|
| All engines work the same way | 116 | 67.1 | 17 | 9.8 | 40 | 23.1 |
| Engines look at all sites | 110 | 63.6 | 32 | 18.5 | 31 | 17.9 |
| Term needs to match index | 99 | 57.6 | 32 | 18.6 | 42 | 23.8 |
| Gathers sites by using a ____ | 25 | 14.6 | 16 | 9.4 | 131 | 76.0 |
| Or retrieves _____ than and | 108 | 62.4 | 31 | 17.9 | 34 | 19.7 |

stood that each search engine operates differently, although almost 10 percent of participants thought search engines were all the same and 23 percent did not know whether they were all the same. Eighteen percent believed that search engines peruse all sites on the Web, and another 18 percent were unsure whether they do. Only 58 percent of participants knew that terms typed into a search engine need to match the indexed sites of that engine in order to be returned. The majority of respondents (62%) understood that the Boolean operator OR retrieves more results than the operator AND. Unfortunately, this means that more than a third of the participants answered incorrectly or did not know.

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Two questions asked the participants to describe what a search engine would do when given a particular search query. These questions assessed the participants' semantic knowledge of a search engine by asking them to describe, in their own words, what goes on inside the system when a command is executed.[44] On the pretest, participants generally were unsuccessful in describing their semantic knowledge, scoring a group mean of 2.87 points out of a possible 12 (standard deviation = 2.93; range = 1, 10). Sixty participants (35%) received no points for this section. Participants who did respond were slightly more likely to include a description of AND as an intersect (45%) than to include OR as a join (41%). Most participants (61%) did not include all of the terms included in the question, opting, instead, to describe what the engine would do with just one or two terms.

Syntactically, participants tended to construct very simple queries with a mean of three terms per query. Boolean operators were used by 31 percent of the participants, with AND used more often than OR. The majority of participants (87%) failed to include any variable terms (terms not included in the question) in their queries.

### *Pretest/Posttest Comparison*

A series of paired t-tests was run to compare pre- and posttest scores for declarative knowledge, syntactic knowledge, and semantic knowledge across all instructional materials. Scores for declarative knowledge could range from 0 to 5; scores averaged 2.63 on the pretest and 3.98 on the posttest. The difference between the means was statistically significant ($t$ = 12.675, df = 172, $p < .05$). Scores for syntactic knowledge could range from 0 to 18; scores averaged 5.54 on the pretest and 8.88 on the posttest. The difference between the means was statistically significant ($t$ = 13.751, df = 172, $p < .05$). Scores for semantic knowledge could range from 0 to 12; scores averaged 2.87 on the pretest and 5.54 on the posttest. The difference between the means was statistically significant ($t$ =

**TABLE 2**
**Pretest And Posttest Scores by Types of Knowledge**

| | | Test results | | | |
|---|---|---|---|---|---|
| | | Pretest | | Posttest | |
| Type of Knowledge | n | Mean | S.D. | Mean | S.D. |
| Declarative knowledge | 173 | 2.63 | 1.34 | 3.98 | 1.05 |
| Syntactic knowledge | 173 | 5.54 | 2.48 | 8.88 | 2.87 |
| Semantic knowledge | 173 | 2.87 | 2.93 | 5.54 | 2.91 |

| Type of Knowledge | n | Mean | S.D. | t |
|---|---|---|---|---|
| Declarative knowledge | 173 | 1.36 | 1.41 | 12.675* |
| Syntactic knowledge | 173 | 3.34 | 3.19 | 13.751* |
| Semantic knowledge | 173 | 2.67 | 3.18 | 11.043* |

S.D. = Standard Deviation
*$p < .05$

11.043, df = 172, $p < .05$). These findings lead to the conclusion that the instructional method, regardless of the type of instruction, served to increase participants' scores on declarative, syntactic, and semantic knowledge. (See table 2.)

***Hypothesis #1: Semantic Knowledge Acquisition***

To test the first hypothesis, "There will be significant differences in semantic knowledge acquisition among participants receiving different instructional treatments," two questions on the pretest and two questions on the posttest asked the participants to describe what a search engine would do when given a particular search query. Analysis of covariance (ANCOVA) was used to analyze posttest scores for semantic knowledge across the different instructional materials using prior semantic knowledge as a covariate (Model F = 7.69, df 5/172, p < .05). The results failed to support Hypothesis #1; there were no significant differences in semantic knowledge acquisition among participants receiving different instructional treatments when adjusting for pretest scores. (See table 3.)

***Hypothesis #2: Correlations among Types of Knowledge***

For the pretest, there was a positive correlation ($r$ = .335) between declarative scores and syntactic scores, a positive correlation ($r$ = .278) between declarative scores and semantic scores, and a positive correlation ($r$ = .298) between syntactic scores and semantic scores. The correlations are considered moderate to low, and all are significant ($p < .05$).[45]

For the posttest, there was a positive correlation ($r$ = .310) between declarative scores and semantic scores and a positive correlation ($r$ = .279) between syntactic scores and semantic scores. The correlations are considered moderate to low, and all are significant ($p < .05$).[46] No statistically significant correlation was found between posttest declarative scores and posttest syntactic scores.

**TABLE 3**
**ANCOVA for Semantic Knowledge**

| | Covariate (Pretest) | | | Posttest | | |
|---|---|---|---|---|---|---|
| | | | | Unadjusted | | Adjusted |
| Group | n | Mean | S.D. | Mean | S.D. | Mean |
| Example | 59 | 1.52 | 1.36 | 5.14 | 2.65 | 5.07 |
| Conceptual models without illustrations | 61 | 1.16 | 1.48 | 5.69 | 2.86 | 5.88 |
| Conceptual models with illustrations | 53 | 1.72 | 1.55 | 5.81 | 3.25 | 5.63 |

S.D. = Standard Deviation

**TABLE 4**
**ANCOVA for Syntactic Knowledge**

| | Covariate (Pretest) | | | Posttest | | |
|---|---|---|---|---|---|---|
| | | | | Unadjusted | | Adjusted |
| **Group** | **n** | **Mean** | **S.D.** | **Mean** | **S.D.** | **Mean** |
| Example | 59 | 5.54 | 2.34 | 9.51 | 2.82 | 9.51 |
| Conceptual models without illustrations | 61 | 5.41 | 2.25 | 8.57 | 2.73 | 8.60 |
| Conceptual models with illustrations | 53 | 5.70 | 2.90 | 8.53 | 3.00 | 8.45 |

| **Source of Variation** | **df** | **Sum of Squares** | **Mean Square** | **F** |
|---|---|---|---|---|
| Pretest (covariate) | 1 | 104.58 | 104.58 | 14.19* |
| Treatment | 2 | 39.55 | 19.78 | 2.68 |
| Residual | 168 | 1230.41 | 7.37 | |

*$p < .05$
S.D. = Standard Deviation

The positive correlations between syntactic knowledge and semantic knowledge on both the pretest and the posttest support the second hypothesis, "Syntactic knowledge will correlate with semantic knowledge."

***Hypothesis #3: Syntactic Knowledge Acquisition***

To test the third hypothesis, "There will be significant differences in syntactic knowledge acquisition among participants receiving different instructional treatments," three questions on the posttest asked the participants to write down what they would type into a search engine given a particular topic. Each query was assessed 0–2 points in three categories: accuracy of concepts identified, inclusion of variable concepts, and accuracy of Boolean expression. Analysis of covariance (ANCOVA) was used to analyze posttest scores for syntactic knowledge across the different instructional materials using prior syntactic knowledge as a covariate (Model $F = 5.00$, df 5/172, $p < .05$). The results supported Hypothesis #3; there were significant differences in syntactic knowledge acquisition among participants receiving different instructional treatments when adjusting for pretest differences.

Post hoc analysis using Scheffe pairwise comparisons showed significant differences between the Examples group and the Conceptual Models with Illustrations group ($F[2, 167] = 14.19$, $p < .05$) when testing for syntactic knowledge. The Examples group had an adjusted mean of 9.51 on the posttest; the Conceptual Models with Illustrations group had an adjusted mean of 8.45; and the Conceptual Models without Illustrations group had an adjusted mean of 8.60. These results failed to support the proposition that participants receiving instruction incorporating a conceptual model with illustrations would have the highest scores on the posttest, those who received instruction incorporating conceptual models without illustrations should have the next highest scores and participants who receive instruction by example are expected to have the lowest scores. (See table 4.)

***Declarative Knowledge in Relation to Instructional Materials***

Although declarative knowledge was not hypothesized to affect syntactic knowledge, it may serve as an indicator of general system knowledge; therefore, analyses were run to determine what participants knew about search engines. Answers to each declarative knowledge question on the pre- and posttest were analyzed to evaluate the participants' knowledge of search engines before and after the instruction. The total number of correct answers to every question increased between the pre- and posttest, and the number of participants responding "I don't know" decreased. An area of caution here is that use of the pretest may have conditioned the participants to look for particular pieces of information and this may be reflected in the declarative knowledge posttest scores. (See table 5.)

ANCOVA was used to analyze posttest scores for declarative knowledge across the different instructional materials using prior declarative knowledge as a covariate (Model F = 14.82, df 5/172, $p < .05$). Post hoc analysis using Scheffe pairwise comparisons showed significant differences among the Examples group (adjusted mean of 3.36) and both the Conceptual Models without Illustrations (adjusted mean of 4.33) and the Conceptual Models with Illustrations (adjusted mean of 4.27) groups when testing for declarative knowledge ($F[2, 168] = 25.81$, $p < .05$). These results are not surprising because the information needed to answer two of the questions was not included in the instruction by example (terms typed into a search engine need to match the indexed sites of that engine in order to be returned and the name commonly given to the program that gathers Web sites and returns them to the search engine). (See table 6.)

**TABLE 5**
**Comparison of Pretest/Posttest Answers for Declarative Knowledge**

| | Pretest | | | | | | Posttest | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Correct | | Incorrect | | Don't know | | Correct | | Incorrect | | Don't know | |
| Question | n | % | n | % | n | % | n | % | n | % | n | % |
| All engines work the same way | 116 | 67.1 | 17 | 9.8 | 40 | 23.1 | 158 | 91.3 | 15 | 8.7 | 0 | 0.0 |
| Engines look at all sites | 110 | 63.6 | 32 | 18.5 | 31 | 17.9 | 123 | 71.1 | 38 | 22.0 | 12 | 6.9 |
| Term needs to match index | 99 | 57.6 | 32 | 18.6 | 42 | 23.8 | 130 | 75.6 | 30 | 17.4 | 12 | 6.9 |
| Gathers sites by using a ___ | 25 | 14.6 | 16 | 9.4 | 131 | 76.0 | 124 | 71.7 | 21 | 12.1 | 28 | 16.2 |
| Or retrieves ___ than and | 108 | 62.4 | 31 | 17.9 | 34 | 19.7 | 157 | 90.8 | 16 | 9.2 | 0 | 0.0 |

## Discussion

The purpose of this study was to compare three instructional methods to assist undergraduate students in learning to search the Web. Current methods of Web-searching instruction focus on the use of examples and short procedural descriptions. In instruction by example, a learner is given a series of worked-out problems and then asked to solve a new problem on his or her own.[47] Most existing search engine instruction is structured similarly. This provided the first instructional method to be tested: instruction by example. Research based on observations as users searched the Web showed that users who understood how a search engine worked (semantic knowledge) made better use of it and used more appropriate syntax than those who did not have this knowledge.[48,49] This led to an examination of the literature in other domains for ways to increase semantic knowledge and the identification of conceptual models in instruction—the second instructional method tested.[50–53] Participants in some of these studies were found to benefit the most from conceptual models when illustrations of the system were incorporated into the model.[54] This provided the final instructional treatment—conceptual models with illustrations.

**TABLE 6**
**ANCOVA for Declarative Knowledge**

| | Covariate (Pretest) | | | Posttest | | |
|---|---|---|---|---|---|---|
| | | | | Unadjusted | | Adjusted |
| **Group** | **n** | **Mean** | **S.D.** | **Mean** | **S.D.** | **Mean** |
| Example | 59 | 2.66 | 1.37 | 3.37 | 1.11 | 3.36 |
| Conceptual models without illustrations | 61 | 2. 54 | 1.37 | 4.31 | 0.85 | 4.33 |
| Conceptual models with illustrations | 53 | 2.61 | 1.31 | 4.28 | 0.89 | 4.27 |

| Source of Variation | df | Sum of Squares | Mean Square | F |
|---|---|---|---|---|
| Pretest (co-variate) | 1 | 20.22 | 20.22 | 25.81* |
| Treatment | 2 | 18.99 | 9.49 | 12.11 |
| Residual | 168 | 130.88 | 0.78 | |

*$p < .05$
S.D. = Standard Deviation

The results obtained failed to support the first hypothesis that there would be significant differences in semantic knowledge acquisition among participants receiving different instructional treatments. There are at least three possible explanations for the lack of difference. First, all instructional methods may have contributed to an understanding of how the system works; second, the method for assessing semantic knowledge may not have been sensitive enough; and, third, semantic knowledge for a search engine may need to be acquired through interaction with the system, not just reading about it.

Although it is clear that the conceptual model instruction (both with and without illustrations) included information on how the system works, it also is possible that instruction by example included enough information for the participants to infer how the system works. The instruction by example went into detail about Boolean searching and the differences between AND and OR. This description alone may provide enough information for participants to describe the system in a rudimentary manner, which is supported by the low adjusted-mean posttest scores of 5.07 out of 12 for the Examples group (the Conceptual Models without Illustrations group had an adjusted-mean posttest score of 5.88, and the Conceptual Models with Illustrations group had an adjusted mean posttest score of 5.66). It is more likely, however, that the scoring method for semantic knowledge was too heavily favored toward an understanding of Boolean operators. Two of the six points contributing to the total semantic score for each question were awarded to describing Boolean operation and accounted for the majority of points scored on the posttest. This is not to imply that an understanding of Boolean operators is not important for searchers to have; most retrieval systems, including the Web, use Boolean logic during a search, so understanding these concepts is critical to search success.[55,56] Rather, it may be that the scoring method is not sensitive enough.

**The fundamental goal of the study was to investigate ways for undergraduates to more easily retrieve information from a search engine.**

The low adjusted-mean scores for semantic knowledge mentioned above suggest another explanation for the lack of difference. It may be that semantic knowledge for search engines is best acquired by *using* the system rather than simply reading about it. Mayer's series of experiments for acquiring system knowledge generally focused on systems other than computers, for example, radar, camera, density, brakes, the nitrogen cycle.[57] In those studies, paper-based materials were used to describe the systems. This was the basis for the present study. To date, there are no studies that compare print-based instruction with practice and print-based instruction without practice. However, several researchers in the field of information science have suggested that system knowledge is best acquired during use of the system and that prolonged use increases proficiency.[58–61] In particular, Cecilia Katzeff found that practice in retrieving information from a database system resulted in increased proficiency in using the system and that participants reporting increased comfort levels with the system.[62] Marvin Wiggins also has reported that librarians who develop information retrieval instruction recommend at least one individualized search session at the computer after an introduction to searching fundamentals.[63] More research is needed in this area.

The findings of this study do not provide evidence that a conceptual model of a search engine is more effective than instruction by example in contributing to semantic knowledge, although a conceptual model may be effective in increasing understanding of data sets. Further research is needed on whether semantic knowledge of a search engine is best acquired through practice with the system and whether this scoring rubric is an accurate way to determine semantic knowledge.

The fundamental goal of the study was to investigate ways for undergraduates to more easily retrieve information from a search engine. This ultimately comes down to being able to interact with the system in an effective manner—to be able to formulate a syntactically appropriate search query to enter into an engine. After instruction, participants in the study increased the number of search terms used and the number of Boolean operators used. The number of search terms increased with a mean of 3.19 terms (s.d. = .71) for the first question, 4.05 (s.d. = 1.25) for the second question, and 4.55 (s.d. = 1.28) for the third question. Boolean operators were used in the posttest by 79 percent of the participants (n = 137), with AND (n = 130) used more often than OR (n = 72). Of these, only four percent were used incorrectly. This indicates that across all instructional materials, participants increased in the number of appropriate terms included in the query and were more likely to include Boolean operators. Both of these tactics would lead to a more precise search query and more relevant sites returned.

In this study, it appears that instruction by example was the most effective method for increasing syntactic knowledge. There are three possible explanations for this finding. First, participants in the conceptual model treatments did not attend to all of the relevant information; second, participants in the conceptual model treatments were presented with too much novel information, resulting in cognitive overload; and third, instruction using worked examples is sufficient for syntactic knowledge acquisition.

With the design of the study involving no direct contact between researcher and participants other than through the written materials, it is impossible to ascertain what parts of the instruction the users attended to. It is possible that participants in the conceptual model treatments may have perceived information that described how the search engine handled the search string as extraneous and chose to ignore it. However, two factors make this unlikely. First, participants who received the conceptual model materials spent more time on task than did those who received instruction by example. The Conceptual Models without Illustrations group spent a mean of 14.9 minutes on the instruction and posttest (s.d = 3.20) and the Conceptual Models with Illustrations group spent a mean of 15.9 minutes on the instruction and posttest (s.d = 3.64) whereas the Instruction by Example group spent 13.21 minutes on the instruction and posttest (s.d. = 3.21). Had the conceptual model groups ignored the extra information provided, the mean times would have been closer together. Second, the scores on the posttest differ. If the participants had simply paid attention to the examples portion of the instructional materials, the scores on the posttest would not have been significantly different.

A second possible explanation is that information included in the conceptual model treatments on how a search engine works interfered with the acquisition of the syntactic information from the example provided. In describing his cognitive load theory, John Sweller referred to this as dividing the learner's attention between the acquisition of two separate schemas that would result in working memory overload.[64] The participants may have split their attention between what needed to be entered into the engine and what was going to happen after that. One then would expect the semantic knowledge posttest scores for the participants in the conceptual model treatments to be higher; this was, in fact, the case. For semantic knowledge, the Conceptual Models without Illustrations group had an adjusted-mean posttest score of 5.88 and the Conceptual Models with Illustrations group had an adjusted-mean posttest score of 5.66 whereas the Examples group had an adjusted-mean posttest score of 5.07. This may indicate that the conceptual model groups were working to acquire two different types of knowledge that are not closely related. This is supported by the low correlation between semantic and syntactic knowledge found in this study.

Another possible explanation for the differences between the groups is that instruction by example may be sufficient for acquiring syntactic knowledge. There is a long history of research involving worked examples.[65] Worked examples include a problem statement and a procedure for solving the problem, which are meant to show how other similar problems might be solved. Most of this research has been done with mathematics and physics instruction. In general, worked examples are associated with early stages of skill development.[66] A preliminary exploration of this was done in the present study. Participants with low syntactic knowledge on the pretest (those who scored in the lowest 10% of participants) were broken out, and ANCOVA was used to analyze posttest scores across the different instructional materials using the pretest as a covariate. Significant differences were found ($F[2,24] = 3.696$, $p < .05$). Post hoc analysis using Scheffe pairwise comparisons revealed that participants in the Examples group had a higher syntactic score (adjusted mean = 8.81) than participants in the Conceptual Models with Illustrations group (adjusted mean = 5.57). It may be that instruction by example may be most effective for low prior knowledge learners who are at the beginning of their learning and that later emphasis on semantic knowledge may be beneficial. This area needs further research.

## Conclusions

This study is a critical first step in researching effective instructional strategies for Web searching. The number of users accessing the Web is increasing, as is the amount of information on the Web. Although efforts are being made to increase the usability of the search engine itself, progress has been slow.[67,68] Effective instruction may be the key to increasing the return of relevant results and decreasing user frustration while searching the Web. The dearth of knowledge on effective methods of instruction for Web searching led to this study. Although the results are not conclusive, suggestions can be made as research continues in this area. First, partnering with instructional designers who have a broader understanding of learning theories and instructional methods may result in innovative instructional methods. In pairing educational theorists with librarians and information specialists, each party can bring strengths to the table that the other does not have. Second, research in the area should continue. Only through effective testing and sharing of results will the field be able to move toward identifying best practices.

## Notes

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